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SHELF LIFE MODELLING FOR FIRST-EXPIRED FIRST-OUT WAREHOUSE MANAGEMENT

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SUMMARY

In the supply chain of perishable food products large losses are incurred between farm and fork. Given the limited land resources and an ever growing population, the food supply chain is faced with the challenge to increase their handling efficiency and minimise postharvest food losses. Huge value can be added by optimising warehouse management systems, taking into account the estimated remaining shelf life of the product, and matching it to the requirements of the subsequent part of the handling chain. This contribution focusses on how model approaches estimating quality changes and remaining shelf life can be combined in optimising First-Expired First-Out cold chain management strategies for perishable products.

To this end shelf life related performance indicators are used to introduce remaining shelf life and product quality in the cost function when optimising the supply chain. A combinatorial exhaustive search algorithm is shown to be feasible as the complexity of the optimisation problem is sufficiently low for the size and properties of a typical commercial cold chain. The estimated shelf life distances for a particular batch can thus be taken as a guide to optimise logistics.

Key words: cold chain optimisation; FEFO; postharvest food loss reduction; shelf life modelling; warehouse management

INTRODUCTION

The globalisation of supply networks makes the task of supply chain management more and more challenging and often requires strategic shifts to continue to meet market demands. In the supply chains for perishable products, such as processed and fresh food products, the partners have a shared responsibility of minimising quality losses to deliver high quality products to the end users. In spite of their efforts a large portion of what is produced is never consumed. In the case of fresh fruits and vegetables the combined postharvest loss and waste can reach as high as 50 % of the produced volume [1].

Food loss refers to the decrease in edible food mass at the production, post-harvest and processing stages of the food chain due to processes like weight loss, microbial rots, diseases and insect damage. Food waste, a symptom merely characteristic for developed countries' consumerist lifestyles, refers to the discard of products not meeting set quality standards, waste generated during processing, surpluses during catering and consumption, and unsold volumes running out of shelf life due to a mismatch between supply and demand. Some of these factors are inherent to the perishable character of the food products while others are clearly economically and socially determined. To be able to sustain a growing world population with enough food within the restriction of limited land resources the global supply chains for perishable products, such as processed and fresh food products, should above all focus on reducing existing food loss and food waste by intelligent food logistics [2].

By understanding the behaviour of our food products in response to the handling conditions of the supply chain, logistics can be further improved. To come to a successful integrated chain management approach several international efforts have been developed focusing on the various relevant aspects such as sensor technology to monitor the logistic conditions [3], RFID and GPS technology to enable fast communication throughout the supply chain [4, 5], improved transport modalities to guarantee better climate control [6], new warehouse management approaches dedicated to perishable products [7], shelf life models to predict the product's behaviour [8] or a combination of one or more of these aspects [9]. The ultimate path to optimising perishable food logistics would engage all of the aspects mentioned above while taking the product´s requirements as the central instruction leaflet to shape the supply chain around it.

This contribution focuses on the use of prediction models describing product quality changes during handling and transport and on how this information can be incorporated into warehouse management systems moving emphasis from the classical first-in-first-out towards a first-expired-first-out strategy. By implementing such model-based approach, the flow of perishable goods can be optimised taking into account the expected shelf life of the products. By doing so, unnecessary losses throughout the supply chain can be prevented minimising economic losses as well, while meanwhile clients can be served better by providing them with product meeting their requirements and will also help match the product holding versus demand ratios [10].

Quality in the supply chain of perishables

Concepts of shelf life and Keeping Quality

Quality of horticultural product is largely based on subjective consumer evaluation of a complex of quality attributes (like taste, texture, colour, and appearance), which are based on specific product properties (like sugar content, volatile production and cell wall structure) [11, 12]. What constitutes quality largely depends on the social and economic background of the consumer and the intended usage of the product. Quality can be seen resulting from the concerted action of several quality attributes each based on their own physiological or physical product property. These product properties are generally changing during time, as part of the normal metabolism of the product.

In general, quality decreases with time. In spite of all efforts, postharvest handling will not improve the quality of product; it can only delay the process of quality loss. Only in some exceptional cases one might interpret the changes as an improvement of quality such as in the case of fruit ripening. Depending on the position of the product in the supply chain this might be interpreted as a gain (offering ready-to-eat fruit in a super market) or a loss (fruit becoming too ripe to be shipped to distant markets).

This brings up the concepts of shelf life and keeping quality [13]. Keeping quality refers to the time it takes under real life supply chain conditions before quality falls below some quality limit turning the product unacceptable, while shelf-life is the keeping quality under well-defined storage conditions (e.g. air storage at 18 °C and 80 % relative humidity). Generally the limiting factor with regard to consumer acceptance can be pinpointed to a single quality attribute. To predict keeping quality of a product, monitoring of this single attribute suffices but does not necessarily gives a complete picture of the quality. For this a more elaborate compound quality index is required.

Environmental factors affecting product quality

Quality of perishable products is not a static parameter but is a highly dynamic variable. Depending on the supply chain conditions quality will change over time at varying rates. One of the premises in the perishable food industry is that the physiological, microbial and (bio)chemical processes responsible for quality loss can be suppressed by manipulating the conditions under which the produce is stored, packaged and transported. Generally most emphasis is put towards the control of temperature followed by humidity, and the levels of oxygen and carbon dioxide. To understand the mode of action of these environmental a good understanding of how relevant product properties depend on storage conditions is required.

Temperature is the main factor affecting all (bio)chemical processes through its effects on activation enthalpy and entropy of the underlying reactions [14]. This is valid both for enzymatic and non-enzymatic reactions and therefore applies to a wide range of fresh and processed food products. While low temperatures are often required to extend shelf life, some products (e.g. most tropical fruits) are sensitive to low temperature decay resulting in a reduced shelf life [15]. In addition mechanical cooling goes hand in hand with drying of the air inducing saleable weight loss and often also affecting the products' appearance through wilting or shrivelling [16]. For this reason relative humidity is considered the second most important factor affecting quality. To minimise water loss additional humidification or proper packaging is required. At the same time too high humidity's can induce moistening of for instance dried products and microbial rot of many fresh and processed food products. Hence, relative humidity plays an important role in the conservation of both dry and water rich fresh and processed food products. Given the importance of temperature control in the supply chain of perishable food products one often tries to maintain proper low temperatures throughout the supply chain. Such temperature controlled supply chain is often referred to as a cold chain.

Many food products are derived from living plant or animal parts, and in an unprocessed or minimally processed form these products continue to exhibit an active metabolism required to maintain the biological integrity of the tissue. By proper control of the levels of oxygen (O_2) and carbon dioxide (CO_2) in the storage atmosphere, the product's metabolism can be controlled; by reducing the levels of O_2 and increasing the levels of CO_2, the metabolic rate can be suppressed to the bare minimum, reducing the energy requirements and maximising the product's shelf life [17, 18]. In addition, high CO_2 is known to inhibit microbial growth and thus, from a microbial point of view, contributes to the extension of shelf life [19]. Temperature heavily interacts with the effects of O_2 and CO_2 on both the energy demanding and producing processes. Some quality degrading processes are affected more than others due to the way they depend on the composition of the storage atmosphere [17].

Majority of the sensor applications in the supply chain focuses on measuring and logging the supply chain conditions, across time to be used for first, second and third order supply chain logistics (figure 1). First order logistics use the raw data for compliance issues, to see whether the conditions remained within its prescribed range throughout the supply chain. Going one step further, second order logistics involve processing the monitored data into more useful information such as product quality and remaining shelf life. Finally, third order logistics utilise this derived product quality and remaining shelf life data for smart supply chain decisions such as first-expired-first-out strategies.

FIGURE 1 IS HERE

Warehouse Management for Perishables

Different Strategies

Warehouse management may be viewed as the ability to coordinate both incoming and outgoing goods to limit waste product arriving or leaving the warehouse. At individual warehouses or distribution centres (DC), that serve as a hub to other warehouses, this process has often been mastered and tailored to the individual product and or asset being handled. This is to say that the strategy adopted will have to consider (a) product deterioration rate and (b) product demand [20]. Irrespective of the strategy adopted, the primary aim is to deliver efficiencies across a number of business processes including a reduction in product lead times and also a reduction in product quality losses. Collectively these systems aim at reducing the cost of business operations and adding value to the supply chain. Such systems mainly function by facilitating the flow of information in parallel with the flow of product increasing supply chain transparency. However, these in house systems often function in isolation and may all too often be incompatible with other systems across trading partners across a supply network. This level of incompatibility will lead to disjointed and inaccurate transfers of information across the supply network resulting in an inability to determine the quality and integrity of much incoming goods at an individual DC.

The possibilities to address such issues depend on the level of ownership across the supply chain. If an organisation assumes complete ownership across primary production, secondary processing, and distribution to retail, this facilitates overall process control and makes the task of information sharing much easier. It allows creating information sharing channels across the full supply network where product flows in parallel with its quality and integrity information. This adds an element of transparency both internally within one's own warehouse and also across trading partners as recommended in the Global Reporting Initiative [21]. However, in reality complete supply chain control and, more importantly, asset visibility across all stages is all too often lacking. When evaluating warehouse management strategies it is important to consider that each warehouse is part of a wider supply chain spanning across countries, nations and often continents, and that for each warehouse it is necessary to consider the product's history providing an appreciation of the product.

FIRST-IN-FIRST-OUT AND FIRST-EXPIRED-FIRST-OUT

Common warehouse management and supply chain strategies aimed at efficient product management across the distribution chain include FIFO (First-In-First-Out) and FEFO (First-Expired-First-Out). FIFO is the more commonly adopted approach as it seems to be a logical choice towards asset rotation ensuring stock is shipped out based on its arrival date at each individual DC. This approach requires each individual warehouse or DC to firstly ship products that have spent most time on site irrespective of its remaining shelf life and their final destination [22]. This approach makes the often-criticised assumption that all product arriving on a particular date has the same shelf life potential which all too often is not the case.

A FEFO approach makes different assumptions in terms of product´s shelf life. FEFO will only ship products depending on their shelf life potential in relation to their end destination. It will only ship goods when their expiry date is known thus ensuring only high quality products arrive at destination eliminating product loss during transport. The transition to a strategy of FEFO requires the implementation of information sharing highways across supply chains between trading partners. This enables a data driven supply network on which the DC manager will be more informed of the integrity (shelf-life) of all incoming goods and based on this may then choose to distribute goods based on their remaining shelf life. In these cases DCs will now need to coordinate a "days to destination" approach to logistics. Also, DC managers will be able to view the complete history of a particular product across primary production, secondary processing and distribution which goes beyond a one-step-back, one-step-forward approach.

INTER-COMPANY RELATIONS AND DATA EXCHANGE

Global financial trading platforms rely on the ability to capture, interpret and transmit data across the globe in real time without which the global financial market would not survive. Similarly, commodity supply chains, which once adopted a local approach towards trading, have expanded exponentially and nowadays operate on global scale across time zones and national and international markets as well. To this end, all related activities including sourcing, logistics, processing, storage and distribution need to be adapted to meet such global scale. Key to success is to ensure the physical product and its corresponding information travel in sync across primary production, storage and distribution [23].

To implement these information-sharing highways it is important to develop a "cyber-highway" infrastructure relaying product information across the full supply network. It will bridge the traditional cyber-physical gap between the flow of product and the corresponding flow of information. This cyber-physical link will objectively and accurately provide the essential pre-requisites of a responsive, fully flexible global supply chain essential to address modern day food security issues and to reduce postharvest food losses.

Information resources come in a variety of formats from a variety of sources both internal within the organisation and outside from trading partners or competitors. As a consequence organisations need to synchronise the information traded using similar languages, formats, structuring and information and make this information available in the correct way at the correct time [24]. Only then can trading partners begin to understand their supply chain as this valuable data source rich in management information will help identify value adding and non-value adding processes. From here, one can develop decision supported algorithms to feed information into diagnostic systems, which directly improve the operational efficiency of the supply chain. When used correctly it can (i) provide full chain transparency, (ii) form the architecture of an early identification system and (iii) provide an invaluable recourse in the decision making process at both strategic and exception management.

MODELLING APPROACHES FOR WAREHOUSE MANAGEMENT

A wide range of mathematical models has found their application in the wider food area [25]. Within the framework of developing models for warehouse management three approaches of increasing complexity are considered: (*i*) *Statistical process control* where conditions are monitored and controlled to stay within limits as defined based on statistical concepts, (*ii*) *Generic shelf life models* where the shelf life of a product is modelled as a function of the conditions in the logistic chain, and (*iii*) *Specific quality attribute models* describing a specific quality related property of a specific product (e.g. avocado ripening, strawberry spoilage, and mushroom browning) as a function of the measured logistic chain conditions. The approach of statistical process control forms the foundation for first order logistics while the generic shelf life model and the specific quality attribute model focus on the second order logistics eventually enabling the development of third order logistics strategies.

STATISTICAL PROCESS CONTROL

Statistical process control (SPC), is about monitoring process variables to make sure the process stays constant within certain well-defined specifications [26]. Even though SPC has been widely applied in the area of batch processing [27], the application in food production processes has been limited [28-31] and the application to supply chain logistics is almost non-existing [32]. Applied to the supply chain of perishable food products, the 'process' refers to 'climate control in the supply chain' while the 'variables' are the climate conditions realised. The dimensionality of the control problem is by definition limited, as the number of variables is often limited to the two main factors, temperature and humidity, only.

The control limits are defined relative to the targeted climate conditions, being either optimal conditions based on the product's requirements, or conditions desirable from a managerial point of view. Together they define the range for which the process of climate control is considered to be 'in control'. The control limits can either be defined based on expert knowledge on what variation is deemed acceptable to the product, or based on the inherent variation of the climate conditions during normal operation of the available climate control systems. Both the targeted conditions and the enclosing control limits can remain constant throughout the supply chain or might vary with the position of the food product in the supply chain and the typical requirements and/or limitations in that particular part of the supply chain. Only in case control limits were specified based on the inherent climate variation observed for when the process is 'in control' the approach can be referred to as a true statistical process control. In case the control limits were defined based on expert knowledge, the approach becomes a pseudo kind of statistical process control as the statistical description of stability of the climate conditions is missing. However, from a product point of view the expert based control limits might be more relevant than statistically based control limits.

Statistical process control provides a simple generic approach focusing on quality of the climate control, more than on controlling the quality of a specific food product. Therefore, statistical process control can add value to the supply chain management of perishable food products in situations where specific product knowledge is lacking but where there is an urgent need to guarantee strict climate control. The limited application to date to supply chain management might be due to the fact that the supply chain is owned by various players hampering the data exchange essential to proper statistical process control.

When applying statistical process control for warehouse management, batches of food products can be differentially handled based on their climate history incurred to date relative to the targeted climate conditions and the enclosing control limits. In this approach, products having been exposed to more extreme conditions can be considered the first to expire.

GENERIC SHELF LIFE MODELS

Shelf life models are models where the shelf life of a product is modelled as a function of the conditions in the logistic chain taking into account the overall acceptance by the end users, focusing on the product´s suitability for subsequent marketing. Model predictions give an appreciation of the quality of the incurred logistic handling chain by translating the impact of the logistic conditions on product quality in terms of the days of remaining shelf life. This generic model approach builds on and integrates earlier published work originally focusing on temperature [33] and O_2 and CO_2 [34]. Within the framework of the PASTEUR project this approach was extended to include the effect of relative humidity as well [8]. When quality is interpreted as the additive result of several quality attributes which non-interfering parallel processes degrade, keeping quality (t_{KQ}) at constant environments can be described as:

$$t_{KQ} = \frac{f\left(Q_0, Q_{lim}\right)}{\sum_{i=1}^{n} R_{rel,i} k_i} \quad (1)$$

The exact form of the quality function $f(Q_0,Q_{lim})$ depends on the underlying physiological mechanism and is function of the initial quality (Q_0) and the defined threshold value (Q_{lim}). The quality function can be either complex or simple but it has been shown that for the concept of keeping quality the actual mechanism doesn't play a role [33]. For this reason it is convenient to assume zero-order reaction kinetics. The rate constants k_i (with generally $i \leq 3$) define the rates of change for the involved quality attributes which in the basic concept [33], were assumed to depend on temperature only, following Arrhenius's law [14]. In the extension to include the effect of gas composition (O_2 and CO_2) on the overall metabolic rate of the product, relative respiration rate (R_{rel}) was introduced [34]. In this approach relative respiration was calculated as the ratio between respiration at possibly modified gas conditions applied during transport and storage relative to the respiration at regular air with respiration being modelled using one of the available Michaelis-Menten based respiration models [35]. In case quality degradation is unaffected by modified atmosphere conditions, the effect of respiration can be ignored (R_{rel}=1). In case quality loss relies on multiple quality breakdown processes (i>1) either or not depending on the modified atmosphere conditions, the effect of respiration can be adapted accordingly by using either the actual R_{rel} for $R_{rel,i}$ or by using $R_{rel,i}$ = 1.

The final extension was to include the effect of relative humidity on quality loss. Relative humidity was assumed to affect quality through the absolute water vapour pressure deficit (e_{def}) calculated as the difference between the saturated vapour pressure and the actual vapour pressure [36]. The effect of humidity was incorporated similar to R_{rel} assuming e_{def} is directly affecting the rate constants of quality loss. Again, the different quality breakdown processes might be differently affected by humidity. For those quality degrading reactions not influenced by humidity, $e_{def,i}$ =1; for those reactions that are affected by humidity, $e_{def,i}$ equals the e_{def} as calculated for the current supply chain condition.

Under dynamic supply chain conditions loss of quality is described using a simple differential equation assuming zero-order reaction kinetics following:

$$\frac{dQ}{dt} = -\sum_{i=1}^{n} R_{rel,i} \mathrm{e}_{def,i} k_i \qquad (2)$$

thus taking into account the combined effects of temperature, O_2, CO_2 and relative humidity. From its moment of creation up to the moment a decision maker has to decide on the next step towards the product's future, the change in quality can be calculated following Eq. 2. At each of such decision moments the estimated remaining shelf life can be calculated assuming the product (starting from its current quality Q_s) would, from that moment on, be kept at some constant standard shelf life condition under regular air. Following the assumed zero order reaction kinetics the expected remaining shelf life (t_{SL}) is calculated as:

$$t_{SL} = \frac{\left(Q_s - Q_{lim}\right)}{\sum_{i=1}^{n} \mathrm{e}_{def,i} k_i} \qquad (3)$$

with $k_{1..n}$ depending on the constant shelf life temperature and assuming shelf life takes place under regular air conditions (R_{rel} =1). This assumes that during shelf life the product's respiration rate is no longer inhibited by modified atmosphere gas conditions, but that the humidity during shelf life still plays a role for those processes sensitive to it. The original keeping quality model only incorporating the temperature effect can be seen as a special case of the final model described by Eqs. 2 and 3. The final model version is most versatile given all the relevant supply chain conditions are covered and can be applied to a wide range of perishable products (either fresh or processed, food or non-food).

Specific quality attribute models

Specific quality attribute models describe the evolution of a specific quality attribute for a specific product as a function of the supply chain handling conditions. Which quality attributes are of interest depends on the product under study. While the generic shelf life models do not intend to model the product's physiology but only the time for which a perishable product will remain acceptable to a consumer, the specific quality attribute models do pretend to provide a description of the (relevant) processes going on inside the perishable product resulting in the observed change in quality. By definition such a model will be based on a simplification of the food product and, therefore, will never be 'true' as the only true model is the product itself. The aim of modelling food quality attributes is, however, not to develop true models but to develop valid models; models that are consistent with the current knowledge level and that contain no known or detectable flaws of logic [25]. Also models should be enough detailed for the intended purpose but at the same time enough simplified to give robust manageable models. The basic strategy to develop a suitable model is to apply a systematic process of problem decomposition dissecting the problem into its basic building blocks, reassembling them together leaving out the unnecessary detail. What is essential and what is redundant depends largely on the intended application of the model. In the end the models are to be used to provide an appreciation of the quality of the logistic handling chain and to translate this into the impact the logistic conditions have on product quality attributes.

Given the dynamic conditions affecting food quality attributes the models should be based on differential equations that can deal with dynamic inputs. Kinetic models [37] are most suitable to generically describe complex quality attributes, like fruit mealiness [38], starting from the underlying (bio)chemical, physiological and physics mechanisms. Over the past 20 years in postharvest, where one deals with highly perishable products in relatively complex supply chains, an increasing awareness has been observed of the need for proper mechanistic models to support an integrated quality management [39-41]. While initially models focussed on describing the specific product quality as such, increased emphasis has been put towards developing product quality models applicable to dynamic supply chain conditions [42-45]. Quality of food products is characterised by an inherent large amount of biological variance. To be able to manage the supply chain, clear insight is required in the propagation of such variance during postharvest. In this context increasing effort has gone towards including biological variation as integral part of the quality models ([46], for an extensive review on this topic see [47]).

SHELF LIFE BASED COLD CHAIN OPTIMISATION

The different modelling methods described above can be applied to optimise cold chain management, reducing waste and quality loss. Sufficient insight into a perishable supply chain (or cold chain) enables optimisation of third order logistics (figure 1) in deciding where to ship which product to minimise both waste and quality loss. The discussion on how to define supply chain management compared to more traditional definition of logistics has been hotly debated since 1990s, but had not been truly applied to special requirements of perishable food logistics yet. Cooper et al. believe that the level of coordination between different organisations in the supply chain in terms of all activities and processes should extend beyond traditional logistics [48]. In order to successfully manage and coordinate these activities and processes, some researchers have tried to categorically define the performance components, such as planning and control, organisational structure, product and information flow [49]. Based on the definitions of some of these components, other researchers have laid the theoretical groundwork for analysing supply chain management performance from different perspectives, such as resource or knowledge based view, systems theory, and the more recent stakeholder theory [50, 51].

COLD CHAIN MANAGEMENT

As sensory monitoring technologies advanced over time, many application possibilities opened up to track the temperature of perishable products through storage and transportation in the cold chain [3, 4]. Wireless sensor front-ends, such as active or semi-passive radio frequency identification (RFID) systems, enables accumulation of high-resolution environmental data, such as temperature at pallet or product level, which was otherwise absent in the decision dynamics for cold chain management. On the other hand, back-end systems, such as servers storing the data, run algorithms on the recorded data, such as shelf life prediction, to create actionable knowledge on the quality of products in the cold chain. Finally, such knowledge is utilised to alter decision dynamics to create a better-optimised logistics scenario in the form of distribution algorithms such as FEFO as opposed to FIFO. For instance, an inventory management model proposed in [52] considers the use of RFID front-end technology to monitor temperature and replace the static shelf life based low-resolution models in the literature with a higher resolution (unit level) dynamic model where the demand is quality driven similar to FEFO. However, the authors of that article make it clear that their purpose was not to develop optimal solutions but rather to show using their model provides a “good solution” which can be operationalised. Other researchers have looked into ways to quantify the logistic performance in a perishable supply chain [53]. The generally used logistic network parameters such as consumer and retail demand, shrinkage, transport, etc. are described from a perishable point of view. Simulation results showed a significant increase in food safety, which is only possible by having access to up-to-date product quality in terms of microbial growth.

Since 2001, more than two hundred articles were published discussing how to model and control perishable inventory control [20]. When considering inventory models for perishables, two types which focus on deterioration (as either fixed, age dependent or inventory dependent lifetime) and demand (as either stochastic or deterministic) come into view. Majority of these models consider one or more of the following important performance parameters: price increase or discount based on shelf life, shortages and backordering, single or multi-item control, etc. Optimisation for such models can be prescribed as an ordering policy and for perishables different types of ordering policies were proposed in the literature. For example [54] presents an optimal ordering policy as a Markov decision problem, however, only last-in-first-out (LIFO) and first-in-first-out (FIFO) are considered as two different types of demand, none of which are quite similar to FEFO which is based strictly on the current quality of the product rather than the time it was received. In addition, the performance parameter of this optimal ordering policy is the expected average cost per ordering period, which may or may not correlate well with the ratio of wasted perishables per ordering period.

Other researchers looked at the improvement in opportunity losses when dynamic expiration dates are used instead of static ones [55]. Simulation results showed a decrease of approximately 80% with a dynamic expiration date scenario where the expiration dates of the products are determined based on transport and initial microbial conditions for better pricing or management, though mainly with store level optimisation.

In creating an optimisation strategy to manage a perishable supply chain, one has to make the following observations. First, in [56], where authors claim that different segments of the perishable supply chain might require different strategies, they describe a performance parameter called a product's marginal value of time (MVT) which shows the rate at which product loses value over time in the supply chain. Based on the behaviour of MVT, they show that not only a hybrid model is the best option for minimising lost value, but also that the segments of the perishable supply chain are only slightly linked which means separate optimisation processes can better achieve value maximisation. The second observation is the fact that only less than 10% of the perishable inventory control studies in the literature investigate two warehouses for controlling perishable inventory with others focusing on single warehouse scenarios [20]. Hence, an optimisation algorithm running on such models, no matter what the cost function is, will have to mostly operate on single warehouse scenarios.

Based on these observations, we will now explore the feasibility of a combinatorial exhaustive search algorithm from a DC or warehouse management point of view. In a standard supplier – distributer – retailer supply chain model, given a set of finite inventory, shelf life based optimisation can be defined as:

- ⇨ minimise the number of wasted products, and
- ⇨ maximise the average quality of products delivered to the store.

There are different ways to include an additional performance indicator, such as product quality (or shelf life) in generic supply chain optimisation. In general terms, this is a *combinatorial optimisation* problem, where given a finite set of states the goal is to find the optimal state [57]. The optimal state for a general supply chain is given by a list of Key Performance Indicators (KPIs), which are mostly related to traditional supply chain management goals such as reduced travel times and transport costs or product replenishment frequencies [58]. The KPIs are multiplied by weighting factors to result in the cost function. The process to go from traditional supply chain planning to food specific planning can be described as adding new, shelf life related KPIs to the cost function such as remaining shelf life and product quality.

Optimisation search algorithm

The trivial and perfect solution to such a problem is to find and calculate the outcome for all possible combinations, commonly called as *exhaustive search*. However, in many optimisation problems, this type of categorical search is simply not feasible due to computational requirements. In this section, it is shown that an exhaustive-search algorithm for shelf life based optimisation is possible and the complexity is sufficiently low for the size and properties of a typical commercial cold chain.

In defining the optimisation search algorithm for cold chain, the following information is assumed to be available to create a shelf life inventory at each node in the supply chain:

a. a shelf life model for the transported commodity that operates on recorded supply chain handling conditions (e.g. temperature, humidity, etc.),
b. average supply chain handling conditions profiles of transportation lanes between points in the supply chain.

In an exhaustive search algorithm, a performance variable such as remaining shelf life is calculated for every possible shipment scenario. In order to evaluate the feasibility of applying the exhaustive search in this case, one needs to look at the number of combinations possible given a finite set of retailers, distribution centres and product requests.

If there are N number of distribution centres (DCs) connected to any given store, for n number of requested products, there are $P(n,N)$ number of unique possible ways to divide the number of shipments between the connected DCs. Here, P is called the *partition function* which outputs the number of different ways one can write an integer number as a sum of positive integers [59]. In this case, a modified version is proposed of the partition function, $P(n,N)$, which is the number of different ways one can write n as a sum of only <u>up-to N positive integers</u>. Partition function does not have a closed-form solution, and instead is either calculated via computer methods or approximated by other mathematical expressions, the discussion of which is beyond the scope of this text [60]. Furthermore, since a set of unique numbers of product requests can be distributed in different ways to different DCs, there is an additional probability multiplier, which can be calculated as follows:

$$N_m = \frac{N!}{m_1!m_2!\dots m_k!} \tag{4}$$

where N_m is the number of possibilities given N warehouses and m unique integers in making the sum of total products requested, whereas m_k denotes the number of times k^{th} unique integer appears in the summation. Hence, for n number of product requests, the total number of all possible scenarios can be calculated as follows:

$$P_n = \sum_{i=1}^{L} N_m(i) \tag{5}$$

where;

$$L = P(n, N) \tag{6}$$

and $N_m(i)$ is the number of possibilities for the i^{th} element of the partition function with its own set of unique integers in making up the sum n as shown in Eq. (4). As shown here, the complexity of the exhaustive search algorithm is directly correlated to the complexity of the partition function. There have been studies in number theory to show the asymptotic behaviour of the partition function going back to 1917 – such as the one by Hardy and Ramanujan, which states [61]:

$$P(n) \sim \frac{e^{\sqrt{\frac{2n}{3}}\pi}}{4n\sqrt{3}} \tag{7}$$

This number grows exponentially with increasing number of orders; creating a complexity problem for the exhaustive search approach. However, a key difference is the fact that the specific exhaustive search algorithm for cold chain uses a modified version where n is written as a sum of unique integers only up to the number of DCs. This observation results in a significant reduction in the number of combinations an order can be placed through serving DCs, especially because although multiple warehouses might serve a single retailer, they store different products limiting the number of available DCs when creating the combinatorial table. The number of DCs serving the same perishable product to the retail store thus defines the limiting constraint on the partition function. Figure 2 shows how computationally intensive the search algorithm becomes as a function of the number of DCs and product requests.

FIGURE 2 IS HERE

As expected from Hardy and Ramanujan's findings of asymptotic behaviour, one can observe that a linear increase in the number of DCs serving a particular store results in an exponential increase in the number of combinations. For instance, in the case of a single DC serving the retail store, no matter what the number of requested products is, there is only one way to distribute them to the store. In comparison, the number of combinations increases to 5151 when there are 3 DCs serving the store for the same number of product requests. However, in a real life scenario, assuming pallet level monitoring (where a product equals a pallet), daily order volume for a retail store for a specific perishable product is significantly lower (one to two pallets), as well as the number of DCs which can deliver that product to that store (one to two DCs) thus resulting in a sufficiently low number of combinations to make a full exhaustive search possible.

Once all the combinatorial possibilities are identified, a front-end distribution logic such as;

a. FIFO – ship the products in the order that they are received at the DC,
b. FEFO – ship the products based on their dynamic expiration dates calculated from application of shelf life prediction algorithm to recorded temperature,
c. Any other distribution logic such last-in-first-out (LIFO) or variations of FEFO with local constraints,

is applied exhaustively on all shipment configurations, shelf life inventories are updated at each node in the cold chain and performance indicators such as the number of wasted products or average product quality are calculated to form the global optimisation matrix. As previously mentioned, in a real life scenario, there are other KPIs to consider but the optimisation algorithm is flexible in that exclusive indicators for perishables, such as shelf life and quality can supplement the former criteria to create an optimisation matrix calculated across all combinations. In fact, an optimal point can be found if a certain weighting function, which defines the relative importance of such criteria with respect to one another, is used.

Conclusions

Many current commercial warehouse management systems offer fragmented solutions and lack the ability to adopt a holistic perspective to supply chain integrity due to an absence of information sharing channels and the necessary tools to obtain relevant environmental data. Given a global need to increase transparency and responsiveness, reduce lead times and enhance security in the perishable food chain, the shift from FIFO to FEFO strategies has gathered significant traction. Most conventional systems estimate shelf life based on an onsite approach and a hand over of information, which in many cases is not based on the actual supply chain history to which the product was exposed.

This article presents the base for an integrated approach in which front-end sensor technologies enable the use of generic shelf life modelling approaches taken from the postharvest research area to alter the decision dynamics in cold chain with state-of-the-art algorithms. By combining this with systems for real-time monitoring of supply chain conditions, the perishable specific supply chain optimisation algorithms can be used to form a strategic response management system optimising product flows taking into account the shelf life inventories and estimated shelf life distances between different nodes in the supply chain. The estimated shelf life distances for a particular batch can be taken as a guide to evaluate the potential of the given batch for all the possible transportation scenarios, while proper confidence intervals should still be considered to account for the omnipresent biological variation limiting the accuracy of the shelf life prediction models.

Although the technical means are available to implement such data driven model-based optimisation approaches in practice, its success will largely depend on the chain wide willingness to participate in and contribute to the information-sharing highways.

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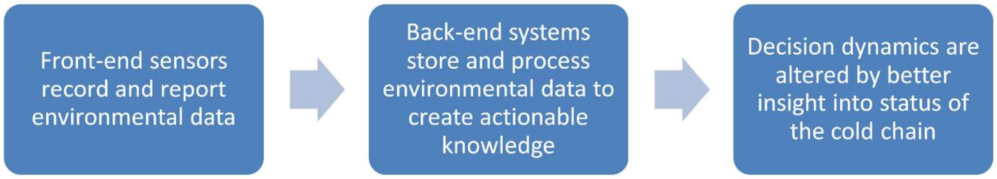
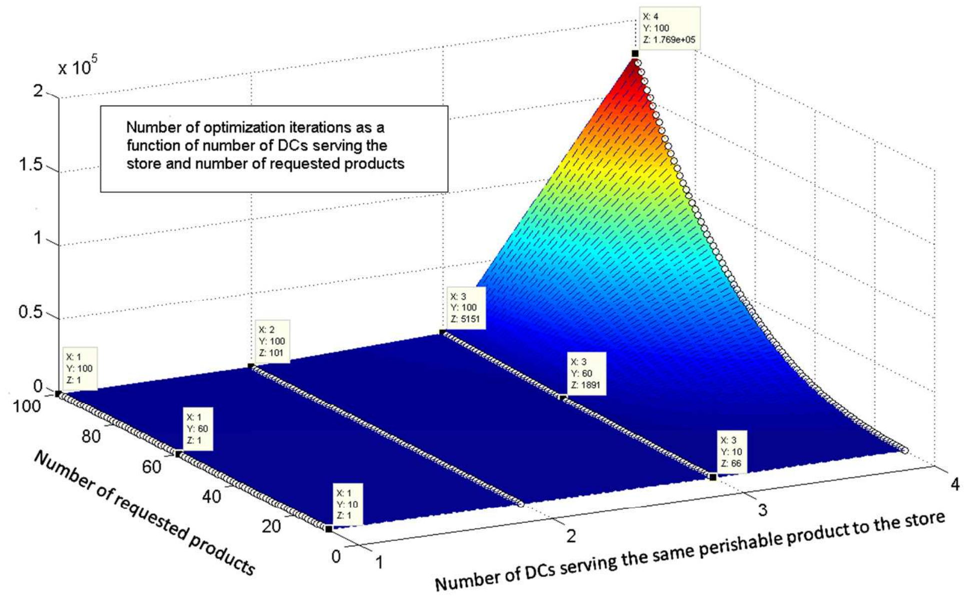
FIGURES

Figure 1 First, second and third order logistics in a monitored cold chain.

Figure 2 Complexity of the exhaustive search algorithm for cold chain optimisation



First, second and third order logistics in a monitored cold chain.
1202x250mm (72 x 72 DPI)



Complexity of the exhaustive search algorithm for cold chain optimization.
430x266mm (72 x 72 DPI)